EXPLORING HIGHLY CITED ARXIV DEEP LEARNING PAPERS

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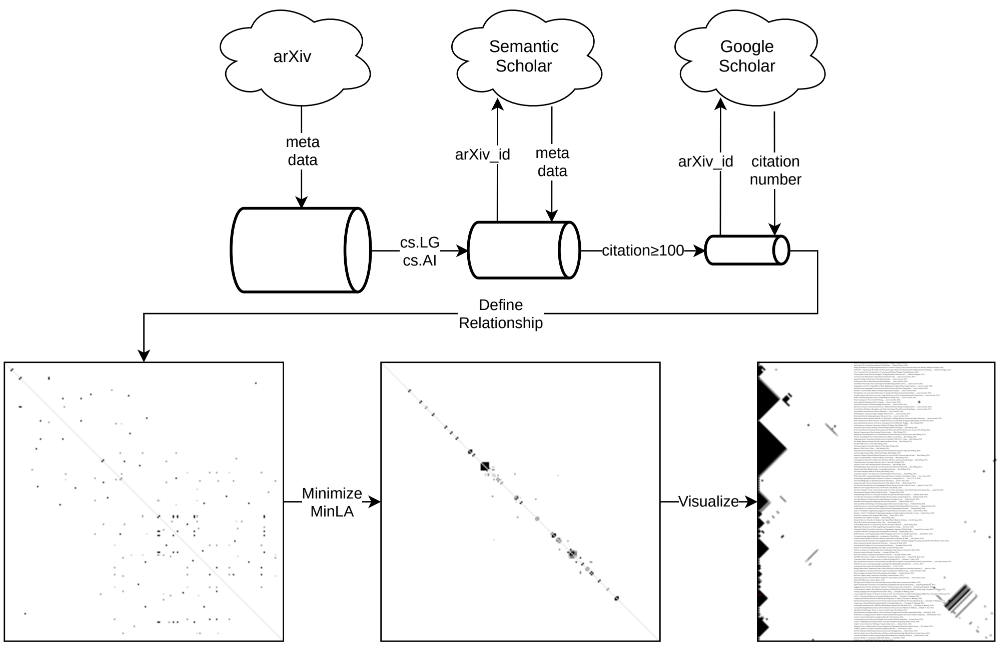

Figure 1: The data processing pipeline.

ABSTRACT

Recently, the number of papers related to Deep Learning has been increasing rapidly. In this paper, we focus on the highly cited arXiv papers from cs.LG (Machine Learning) and cs.AI (Artificial Intelligence) subcategories. We explore the relationship in authors. We reorder the relationship matrix into an approximate block diagonal form by minimizing the linear arrangement (LA) loss function using the Hill Climbing algorithm. We visualize the results as a paper list that can indicate the relationship in authors. We hope this analysis can capture some interesting structures of this research community. Source code is at: `https://github.com/liusida/arxiv_4422`.

Keywords Information visualization · Matrix reordering · Minimum linear arrangement · Block diagonal form · Hill Climbing · GPU

1 Introduction

Recently, the number of papers related to Deep Learning has been increasing rapidly. arXiv.org acts as a central hub for important Deep Learning papers and is open to everyone. Deep Learning papers are mainly distributed in two subcategories: cs.LG (Machine Learning) and cs.AI (Artificial Intelligence). However, the number of papers in these two subcategories has reached over 90 thousand. It is not possible for a human researcher to read all those papers. Thus, a Data Science approach to analyze them is inevitable.

In this paper, we introduce a pipeline that can process the metadata from three sources and reveal some patterns in the data.

First, we harvest the metadata from the arXiv API service and obtain the citation numbers from Semantic Scholar and Google Scholar. We will see, although the total number of papers is big, the number of highly cited papers is relatively small.

We focused on those highly cited papers. We compare the authorships of those papers pairwisely to obtain a pairwise relationship matrix. We reorder the relationship matrix by minimizing the linear arrangement (LA) loss function so that the nodes that have stronger relationships are arranged closer. The optimization can be done both through a basic hill climbing algorithm and a GPU augmented parallel hill climbing algorithm. An approximate optimal solution can be obtained in less than 2 minutes.

We visualize the relationship matrix and observe that clusters are formed, indicating that there are structures in the research community.

Finally, we visualize the results as a sorted list of papers, with a corresponding background image to indicate the community structure.

2 Data

2.1 Retrival

arXiv is the largest hub for open access scientific papers. It also supports the Open Archives Initiative (OAI), so a large volume of metadata can be easily downloaded through the OAI interface. [1]

In April 2021, we downloaded the metadata of 227,842 papers. The analysis we have done is based on these metadata. Our main interest field is Deep Learning. Due to the computational resource constraints, we only processed two arXiv subcategories: cs.LG (Machine Learning) and cs.AI (Artificial Intelligence). There are 93,911 papers in these two subcategories.

We filter the papers by the citation number. The citation number of a paper is a commonly-used indicator. However, arXiv metadata does not include any information about citations, and accurate citation numbers are hard to obtain, so we get the citation numbers from two third-party websites.

The first data source is Semantic Scholar (S2). S2 provides additional metadata including the citation numbers of the scientific papers. [2] We can see from Fig. 2, the citation number follows a power-law distribution, which means there are a few highly cited papers and many papers with much less citations. Among them, 27,317 papers in 93,911 (roughly 29%) have a citation number of zero. Also we can notice from the figure that there is a hard cut-off at 10^4, which might due to their system limitation.

We use the S2 citation numbers to filter out highly citated papers. We keep 4,422 papers with S2 citation numbers larger than or equal to 100 as the highly cited papers.

The second data source is Google Scholar. Google Scholar also provides citation numbers on its website. However, it does not support API retrival due to unspecified reasons. Getting citation numbers from Google Scholar can only be done semi-automatically.

The use of two data sources has both strengths and limitations, so we ensemble two parts together by taking the mean of the two. Fig. 3 shows the distribution of the highly cited papers. [3]

[1] More about arXiv OAI: `https://arxiv.org/help/oa`

[2] More about Semantic Scholar API: `https://api.semanticscholar.org/`

[3] Raw metadata of the 4,422 papers can be downloaded at: `http://star-lab.ai/arxiv/arxiv_4422.tar.gz`

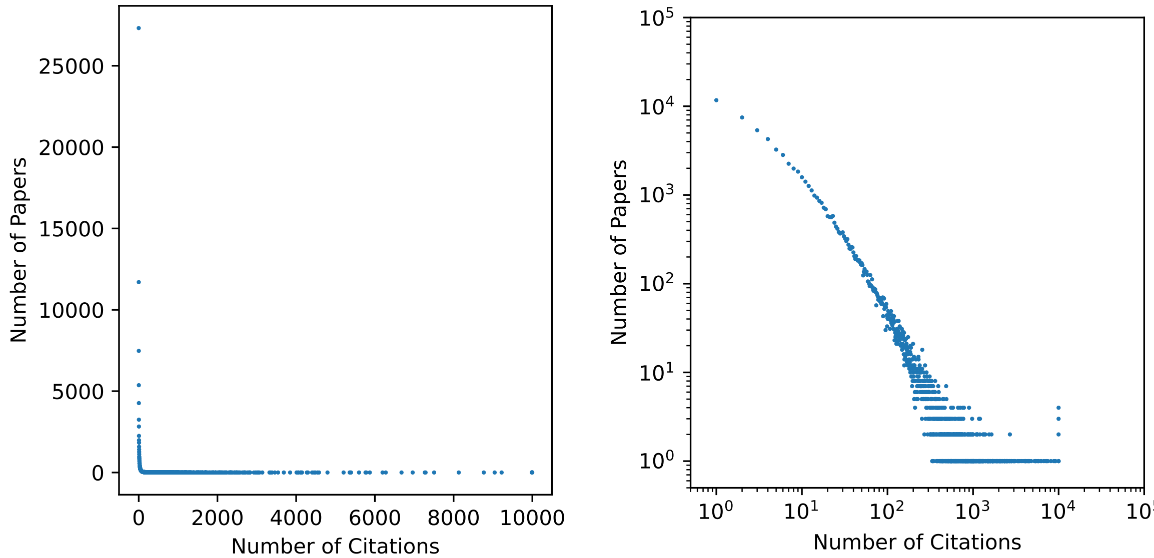

Figure 2: Citation number follows a power-law distribution according to S2. (Left): Normal scale. (Right): Log-log scale excluding the zero-cited papers. Each dot represents *a set of papers* with the same citation number, e.g. the first dot on the left plot represents all papers with 0 citation, and there are 27,317 of them.

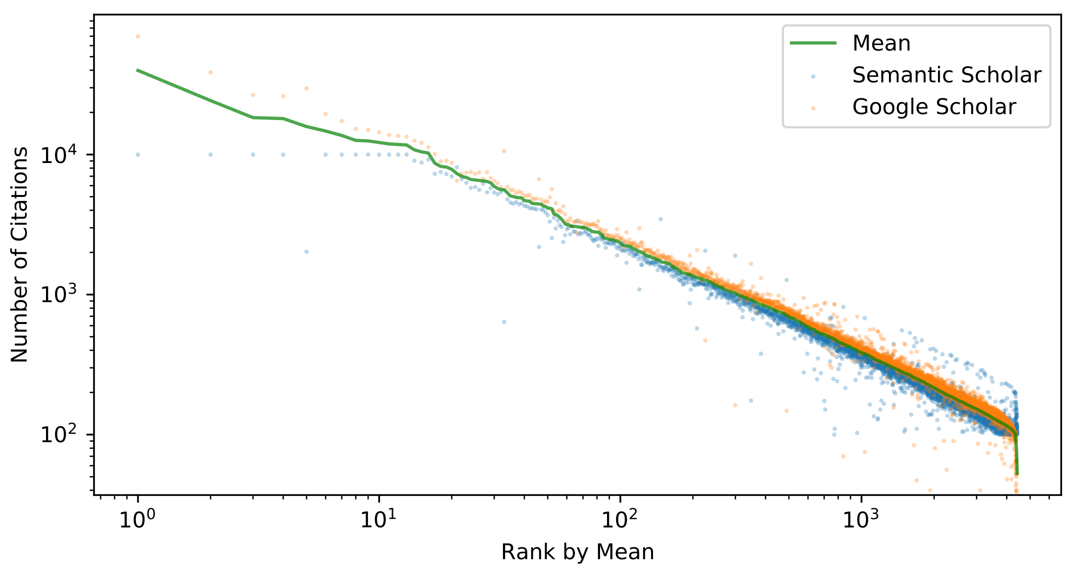

Figure 3: Citation number distribution for highly cited 4,422 arXiv cs.LG and cs.AI papers. The blue dots are the Semantic Scholar citation numbers ($S2$), and the orange dots are the Google Scholar citation numbers (GS). For most of the papers, GS are higher than $S2$. $S2$ are bounded by 10^4, which might due to their system limitation. But GS misses some papers which $S2$ consider them as highly cited. The green line is the mean of $S2$ and GS. Each dot represents the citation number of *one* paper, e.g. the first orange dot represents the citation number (69,774) reported by Google Scholar for the most highly cited paper (Rank 1).

2.2 Relationship Between Papers

Now we have 4,422 highly cited papers. We define a undirected weighted network $G(V, E)$, with its nodes set V to be the set of those papers, and its edges set E to be the set of the relationships between papers.

Our objective is to reveal the structure of the research community. Based on this objective, we define the weights $w_{i,j}$ of the edge between papers based on the overlaps in authorships. We divide the authors of a paper into two classes: (A) the first author and the last author, (B) other authors which are neither the first nor the last author.

There are multiple inconsistencies in arXiv metadata and Semantic Scholar metadata, we tried to correct some errors, but still there are remaining ones. In this case, we use the metadata from arXiv.

Class (A) always at least contains one author, and class (B) could be empty if there are no other authors. We give a weight of 1.0 if class (A) of two papers overlap. Otherwise, we give a weight of 0.5 if class (A) of one paper overlaps with (B) of another paper. Otherwise, we give a weight of 0.3 if class (B) of two papers overlap.

This is an ad hoc method to define the relationships. One can come up with other definitions and the pipeline will still work.

Fig. 4 shows the adjacent matrix of the constructed network G with a random arrangement (which is almost blank).

3 Matrix Reordering

In order to reveal the structure of the network G, we choose to reorder the matrix. There are many ways to rearrange a symmetric matrix, Behrisch et al. [1] provides a good review of those methods. In practice, we notice that many methods will introduce so called the *Off-diagonal Block Pattern* even when there is no such pattern in the data. We consider this as an artifact of the algorithms.

We want to reorder the matrix into an approximate block diagonal form, so that all the papers produced by the same group will be arranged close to each other. We achieve this by minimizing the weighted linear arrangement (LA) loss function:

$$\mathbf{LA}'(G, \pi) = \sum_{ij \in E} w_{i,j} \cdot |\pi(i) - \pi(j)| \tag{1}$$

where π is a one-to-one function $V \to \{1, 2, \cdots, |V|\}$ representing the permutation of the nodes in 1D, a.k.a the arrangement of the matrix; $w_{i,j}$ is the weights of the edge between node i and j.

In this paper, we use a normalized version of MinLA:

$$\mathbf{LA}(G, \pi) = \sum_{ij \in E} w_{i,j} \cdot \frac{|\pi(i) - \pi(j)|}{|V|^2} \tag{2}$$

where $|V|$ is the number of nodes.

This is known as the minimum linear arrangement (MinLA) problem. The MinLA problem was introduced in 1973 as the *optimal linear ordering problem* [2]. It is a special case of the *quadratic assignment problem*, where every node is in a line and have equal unit distance to it's neighbors. It is proved to be a NP-complete problem [3], One should not expect to solve a large scale NP-complete using exact methods, e.g. [4] only works with no more than 20 nodes. Petit [5] has thoroughly introduced some heuristic methods that can provide approximate optimal solutions to the MinLA problem, including the hill climbing method.

A basic hill climbing algorithm can be described in Algo. 1.

Algorithm 1 Hill Climbing

```
while not Terminated:
    i, j ← random()
    if swapCanReduceLA(i,j):            ▷ This can be done in O(|V|).
        swap(i,j)
```

To take advantage of the power of parallel computing, we propose a GPU augmented hill climbing method, described in Algo. 2.

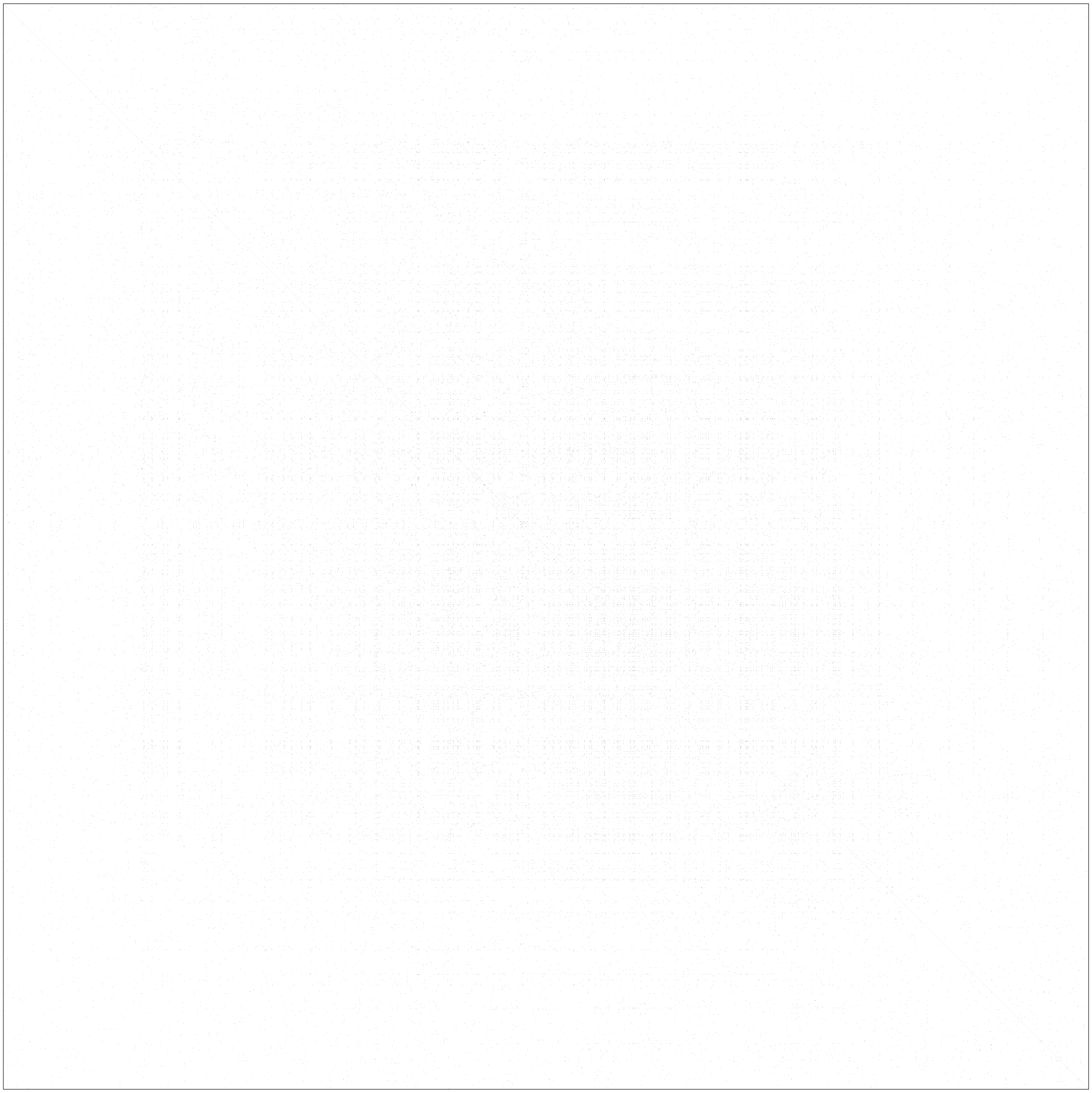

Figure 4: The relationship matrix in a random arrangement before matrix reordering. Dark grids mean they have values, which represent the author relationships between two papers. The diagonal line is defined to be 1.0. However, a 4422x4422 matrix with a random arrangement is almost meaningless to a human observer. (The image looks almost blank due to the sparsity of the matrix.)

Algorithm 2 GPU augmented Hill Climbing

```
while not Terminated:
    Detect pairs which if swapped will reduce the LA cost        ▷ With 32,768 threads on GPU
    Sort pairs by the gains (the amount that can be reduced)
    Remove conflicted pairs with less gains
    Swap all remaining pairs
    If number of the found pairs is small:
        Double the number of parallel threads for detection until limit hit
```

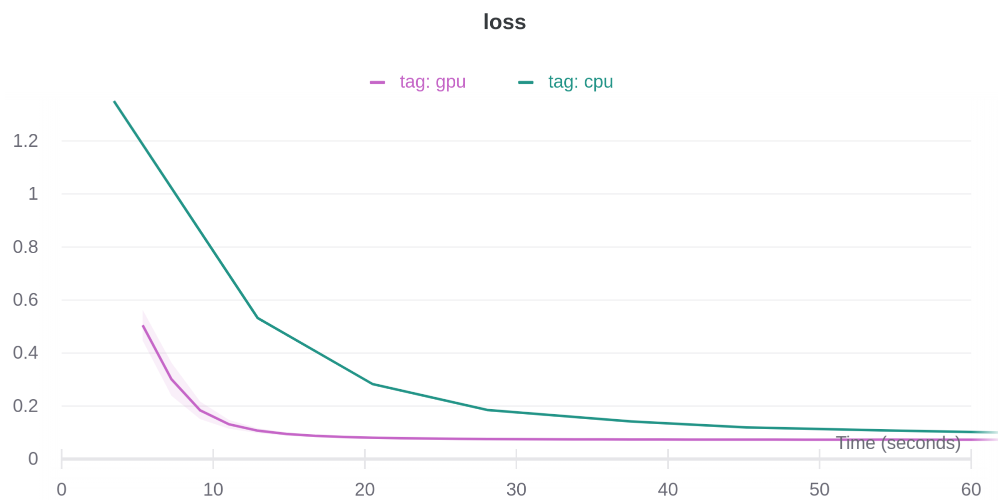

Figure 5: A comparison of the first 60 seconds of the optimization curve of Algo. 1 and 2. Averaged over 100 independent runs. The GPU augmented algorithm is better than the basic algorithm in wall-clock time.

Fig. 5 shows the comparison of Algo. 1 and 2 in wall time.

Both the basic hill climbing algorithm and the GPU augmented hill climbing algorithm are implemented in Python and accelerated by Numba [6]. One instance of Algo. 1 uses one Intel 6230 CPU core. One instance of Algo. 2 uses one Intel 6130 CPU core and one NVIDIA Tesla V100s GPU.

Both methods are fast enough to get reasonably good results in less than one minute, though the GPU augmented version can achieve better solutions in general. One of the results can be visualized in Fig. 6.

However, it still slightly suffers from local optima. In order to get more globally optimal results, one can not rely on running the algorithm for longer.

Our best results are achieved by searching with 100 independent runs with random initialization. However, we observe that the initial states matter more than trying different choices during optimization. Thus, an evolutionary approach [7] searching for better initial states might be better than our random initialization.

4 Visualization

We design a way to visually present the final arranged results. The goal is to easily navigate through with useful visual clues. The final visualization is made as a web page. [4]

On the left, the vertical line is made of the diagonal line of the relationship matrix. The larger the clusters are, the more collaberations are there in those groups.

On the right, they are the reordered list of all papers. One can easily search keywords to locate interesting parts of the list.

5 Discussion

In this paper, we define relationships between papers by the overlap in authors. Future work can explore different relationships, e.g. the interactions of the authors' Twitter accounts, or the similarity in the abstract, etc.

The implementation can be further optimized by using sparse matrix presentation instead of a 2D array.

[4]The final visualization can be accessed at: `http://star-lab.ai/arxiv/`

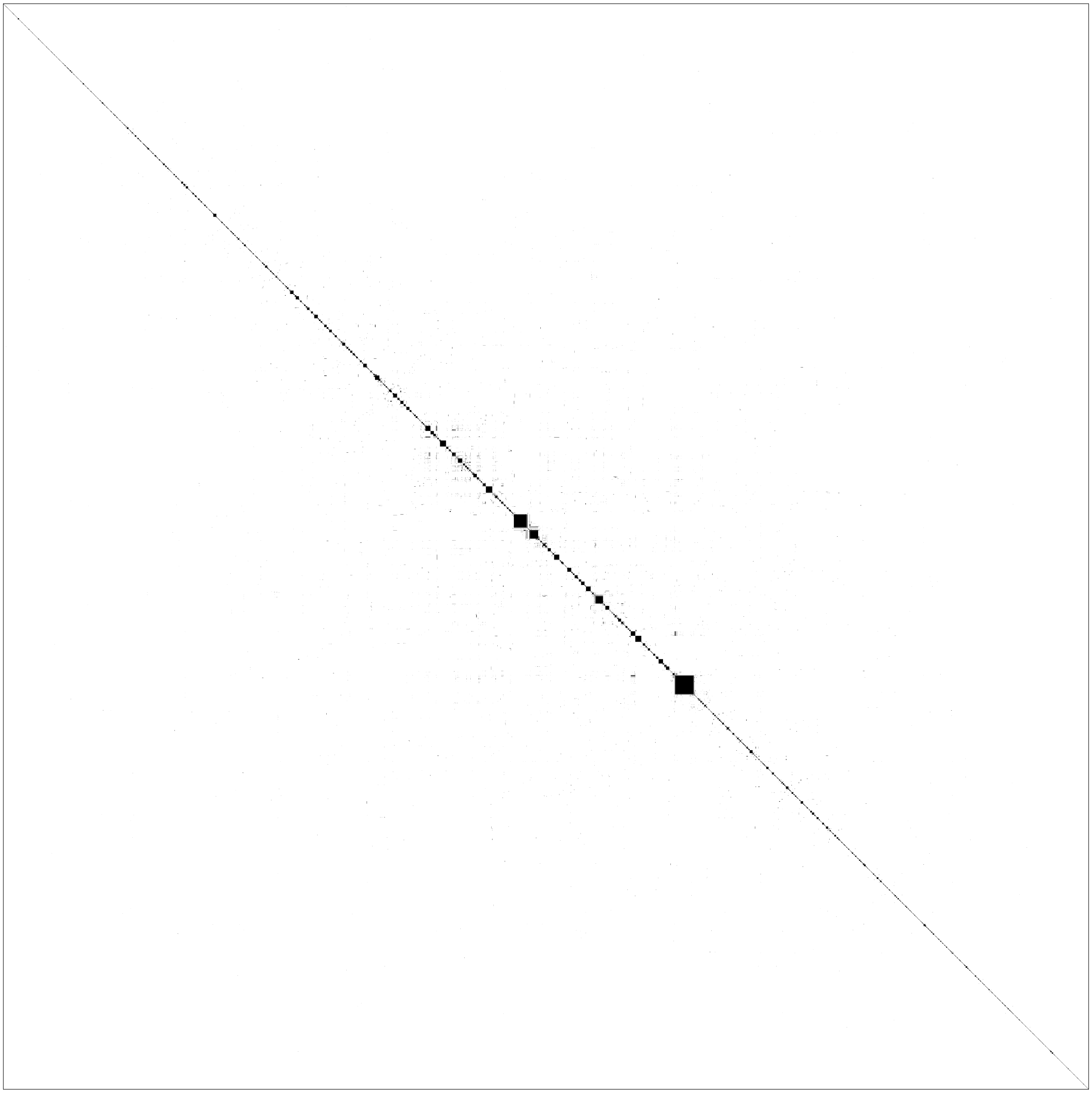

Figure 6: The most optimal solution of Algo. 2 in 100 runs, with LA=0.06596. Computing this solution takes about 4 minutes. Now we can easily observe the structure of the research community. The largest square in the center represents the papers related to Yoshua Bengio; the second and third squares close to each other represents the papers related to Sergey Levine and Pieter Abbeel. Other clusters can be observed.

6 Conclusion

In this paper, we presented a pipeline to process metadata of highly cited arXiv papers in two subcategories: cs.LG and cs.AI. Those metadata comes from different sources. We built a relationship matrix by defining the relationships in authorships. We reordered the matrix by optimizing the LA loss function using a GPU augmented hill climbing method. The results of the optimization reveal the structure of the research community. We presented the final results as a web page to help other researchers to understand this social structure better.

7 Acknowledge

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